

Research Article

Influence of Management Education on Enterprise Scientific and Technological Innovation Based on K-Means Clustering Algorithm

Jun Ma ¹, Zhigang Li,¹ Zichan Liu,¹ Shan Zhang,¹ and Wenling Lai²

¹Guangzhou City Construction College, Guangzhou 510925, Guangdong, China

²Wuchang University of Technology, Wuhan 430223, Hubei, China

Correspondence should be addressed to Jun Ma; marco791@163.com

Received 22 April 2022; Revised 7 July 2022; Accepted 25 July 2022; Published 24 August 2022

Academic Editor: Xuefeng Shao

Copyright © 2022 Jun Ma et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Scientific and technological innovation is the source of the survival and development of enterprises and the key to the realization of the goal of prosperity. In recent years, more and more companies have begun to focus on technological innovation, but the results are not significant, so companies have begun to explore the factors that affect their technological innovation. The management is the helm of the development of the enterprise, the main body of the company's actual production activities, and the direct person in charge of the company's management. Its influence on the innovation of the enterprise is self-evident, and the education level of the management directly determines the manager's ability and vision. However, the current research on management mainly focuses on the position change of management and the rights of management and does not involve the level of education of management. Based on this, this article started from the management education and subdivided it with the K-means clustering algorithm, so as to explore the impact of management education on the technological innovation of enterprises. The experiment showed that there was a significant positive correlation between the educational level of management and the technological innovation ability of enterprises, and the correlation coefficient was 1.521. It fully shows that the management with a higher education background will promote the enterprise to carry out scientific and technological innovation practice and continuously improve the enterprise's innovation ability.

1. Introduction

With the development of science and technology, enterprises pay more and more attention to the integration of technology and products and constantly propose new development plans. However, with the adjustment and upgrading of the industry, there are obvious differences in the investment of enterprises in innovation, which brings challenges to enterprises' innovation planning. Existing researches on the difference of enterprise innovation investment mainly focus on the change of management positions and the rights of management. However, compared with these traditional managers, the level of education of managers can often better reflect the overall quality and ability of managers, so it can also have a greater

impact on the company's innovation decision-making and management.

The long-term development of an enterprise is inseparable from the continuous innovation practice. The management is the leader in the management of the daily affairs of the enterprise, and its education level is often directly reflected in the daily decision-making of the company. Research based on the education level of managers can provide a reference for enterprises to hire relevant management personnel; at the same time, it is helpful for enterprises to assess and motivate management and help to promote the establishment of a more reasonable reward and punishment mechanism. In addition, enterprise scientific and technological innovation is an important part of enterprise management, and it is a key element that determines

the company's development direction, development scale, and development speed. This move can reduce the negative impact of the irrational behavior of company managers on the company and improve the scientific nature of corporate innovation decisions.

After a series of experimental analysis, in the process of clustering division of management education level based on K-means clustering algorithm, when the number of clustering reached 7 times, the clustering result tended to be stable, and the numerical result fluctuated around 2400. At this point, clustering results had the lowest impact on management division. Moreover, the experiment showed that management with higher educational background could approve enterprises to adopt more means to carry out technological innovation, the correlation coefficient was 1.521, and the correlation coefficient between it and the number of patent applications was 1.662. At the same time, the regression coefficient between enterprise innovation input and management with high education background was -0.164 , and the regression coefficient between enterprise innovation input and output and management with higher education was -0.221 , and it was in the horizontal direction of 1%. There was also a significant negative feature at the level, which fully demonstrated the robustness and reliability of the above correlation conclusion. As a result, enterprise management who have experienced higher education will often lead the enterprise to enter the scientific and technological innovation market and continuously improve the enterprise's independent innovation ability.

2. Related Work

With the continuous development of the economy, more and more companies have begun to propose innovation-driven development strategies. At the same time, many experts and scholars have also turned their attention to this area. Yang studied the relationship between work pressure and enterprise innovation cost management. On this basis, he proposed a model to measure the relationship between pressure coefficient and innovation. At the same time, he used the job demand control model to conduct a comprehensive evaluation of employees' mental health, work pressure, engagement, innovation ability, and so on. And then he analyzed the impact of these factors on enterprise technological innovation [1]. Liu took scientific and technological innovation as an intermediate variable and aimed to explore the role of intellectual property protection in the improvement of enterprises' scientific and technological innovation capabilities. In the process, he collected panel data of 80 advanced manufacturing SMEs from 2013 to 2015 and made a detailed analysis of these data [2]. Zhang proposed a plain-text corpus method based on latent Dirichlet assignments, which can automatically construct an ontology in the field of enterprise technology innovation. The method consists of four modules: initial ontology in the field of enterprise technology innovation, preprocessing system, domain-specific terminology mining based on LDA, and related rules defined [3]. Chen aimed to reveal the relationship between firm innovation network and

technological innovation performance from a new perspective. He developed the symbiotic behavior scale and found that symbiotic behavior plays a certain role between the structural characteristics of enterprise innovation network and technological innovation performance. Therefore, he developed the symbiotic behavior measurement scale according to the scale development process and tested the scale using exploratory factor analysis, confirmatory factor analysis methods, and competition models [4].

The above scholars have analyzed the factors that affect the technological innovation of enterprises from different levels, but none of them have studied the impact of management education on technological innovation. K-means clustering algorithm has significant advantages for data classification and mining, so we refer to a series of related literature.

Wang pointed out that disease spot segmentation from crop leaf images is a key prerequisite for disease early warning and diagnosis. In order to improve the accuracy and stability of disease spot segmentation, he proposed an adaptive segmentation method of crop disease images based on K-means clustering [5]. Khan proposed an improved K-means clustering algorithm for intelligent image segmentation, which used an adaptive histogram-based initial parameter estimation process [6]. Li proposed an optimized K-means clustering method and also proposed three optimization principles. At the same time, he pointed out that applying these three principles could minimize the computational cost and improve the computational efficiency of K-means [7]. Allen proposed an improved algorithm for the dependence of the K-means clustering algorithm on the initial cluster center. The algorithm improved the stability and accuracy of the clustering results and sped up the convergence. In the improved K-means algorithm, he selected the initial cluster centers according to the spatial distribution of the data and then sorted the average difference of each sample [8].

The above literature has carried out in-depth research on the K-means clustering algorithm and has carried out relevant optimization and upgrades to the K-means clustering algorithm on the basis of the original algorithm. But for management education, the above scholars have not carried out detailed research. Even if there is, it is a passing area, and the research is not in-depth and detailed enough.

3. Management Education and Enterprise Technological Innovation under K-Means Clustering Algorithm

3.1. Enterprise Technological Innovation. Scientific and technological innovation refers to specific activities used by industrial enterprises in scientific and technological innovation and technology development, including direct expenditures for enterprise research and development activities and all expenditures for indirect research and development activities. Technological innovation is the only way for an enterprise to achieve self-development and innovation. Nowadays, technological innovation capability has increasingly become a key indicator to measure the

comprehensive competitiveness of an enterprise [9]. In the market competition without gunpowder smoke, whoever can first realize technological innovation and technological progress will be the first to seize the market and remain invincible in the fierce competition. Technological innovation is not only the need of a certain region or society, but also the common value pursuit of all mankind. In scientific and technological innovation, the development of science and technology and innovation complement each other. On the one hand, the progress of science and technology will promote the improvement of innovation ability. On the other hand, the improvement of innovation ability will also promote the progress of science and technology to a certain extent [10]. Science and technology not only are used in enterprises, but also cover most fields in society. Figure 1 shows the main application fields of science and technology.

To achieve scientific and technological innovation, enterprises cannot do without the overall innovation in corporate governance thinking. In the process of continuous technological innovation and development, people have gradually summed up several ways of thinking that corporate governance needs to have. These ways of thinking can help us clarify the path and direction of innovation and provide guidance for our scientific and technological innovation experiments.

3.1.1. Innovative Thinking. The innovation of thinking mode is indispensable for enterprises to carry out scientific and technological innovation. Innovative thinking is a kind of thinking gradually formed in the process of scientific and technological innovation, which pays particular attention to the rigour of thinking and usually relies on some specific scientific thinking modes in actual scientific and technological innovation activities [11]. Creative thinking is a pioneering advanced and complex thinking that explores unknown things. It is a kind of original thinking with its own characteristics. Therefore, enterprises can grasp the effective innovative thinking mode in time, which can help enterprises quickly identify the direction of innovation and concentrate all advantages for innovative practice.

3.1.2. Analogical Thinking. Analogical thinking is a way of thinking commonly used in mathematics. Its principle is to compare unfamiliar things with familiar things in order to gain an understanding of new things. However, in the specific innovation practice, enterprises should realize that analogical thinking is only a reasoning method for researching problems, and the cognition provided by it is only a possibility, not a certainty. Therefore, for the final result, the enterprise must conduct a rigorous practice test, so that the result can be adopted. But nonetheless, it is invaluable that the possibilities offered by analogical thinking expand ideas for problem-solving.

3.1.3. Associative Thinking. Associative thinking is a kind of thinking activity produced by the divergent association of the characteristics or attributes of different things [12].

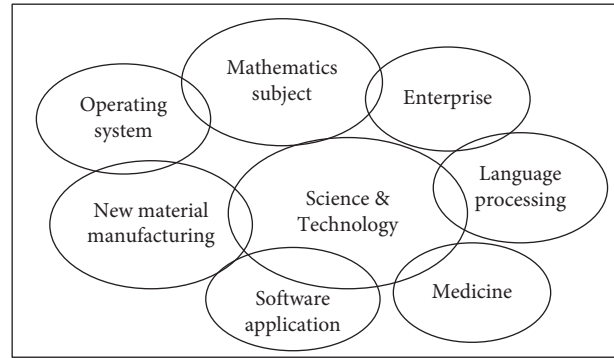


FIGURE 1: Application areas of science and technology.

Associative thinking plays a very important role in daily innovation practice, because associative thinking refreshes the way to see the world and provides us with a reference for innovation. The use of associative thinking by enterprises can fully mobilize their enthusiasm for innovation, provide guidance for other ways of thinking of enterprise innovation, and continuously promote the progress of enterprises' scientific and technological innovation capabilities.

3.1.4. Leap-Forward Thinking. Leap-forward thinking means that after we have thoroughly understood the core concepts and combined them into knowledge ability units, the next thing we need to do is to use the cognition that we can understand better to connect them and memorize them. For example, in business analysis, the marginal benefit, scale effect, and the marginal interpersonal communication field and crowd size in the communication model can be combined and memorized, so as to consolidate the cognition of core concepts and exercise the divergent ability of one's own thinking.

3.2. Enterprise Management. Enterprise managers are the main body of production and operation activities of enterprises [13]. In daily business operation, managers play a leading role in corporate governance and decision-making activities by relying on their own quality and professional knowledge and skills. In the previous corporate structure, the general manager was always the one person in charge of the management, who was responsible for the decision-making and formulation of the company's large and small affairs. Although they mainly manage subordinate employees, they also shoulder specific tasks. However, in modern corporate management activities, the work and functions of the management are artificially subdivided, and the management often completes organizational activities by several managers through coordinating and monitoring the work of others. Figure 2 is a management organization chart of a modern enterprise.

According to the requirements of management, the enterprise management organization divides the production administrative command system of the enterprise according to the principle of division of labor and cooperation, clearly

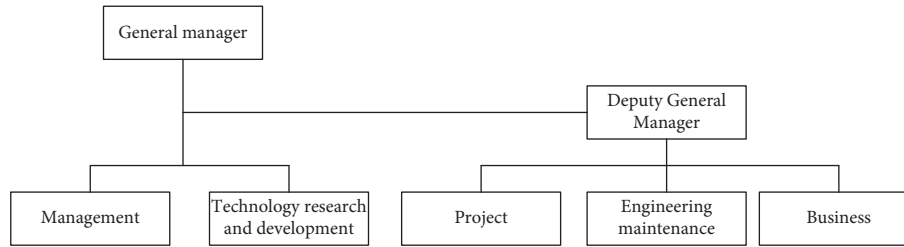


FIGURE 2: Organizational chart of enterprise management.

defines the responsibilities, authority, obligation, and information communication mode of each management level or link, and correspondingly configures a certain number of competent management personnel. Management often has a multilevel structure, which is generally divided into general management, middle management, and senior management. General management is the managers at the lowest level, and they are often managers engaged in production, sales, and other services. General management is the company's grass-roots reserve cadres; they often have the potential to become senior managers. The middle management is the backbone of the company. Their main job is to transmit, that is, to receive tasks from senior management and then assign them to ordinary management. They also oversee the work of ordinary management and accept leadership from senior management. The senior management is at the helm of the enterprise. They formulate the development strategy of the enterprise according to the market environment and use the corporate image to contact the outside world and then adjust the development direction of the enterprise according to the latest changes in the market in real time [14]. They are the core figures of the operation of the enterprise and the executors of accomplishing the goals of the board of directors. An excellent senior manager not only has excellent business ability, but also needs to have a certain financial level.

Because senior management often has extraordinary status and unparalleled power in the company, the object of enterprise management in this paper mainly refers to the management [15]. On the one hand, the senior management decides the direction of the enterprise and has the right to make decisions on all matters of the enterprise. On the other hand, the self-quality and ability of senior managers are the external embodiment of the company, and taking them as the research object can better discover the problems existing in the development process of the enterprise. At the same time, the role of middle management in the enterprise has been a controversial topic. Some researchers believe that the middle management in the company only acts as a transmitter of information and cannot create any value for the enterprise. The other researchers believe that middle management is an indispensable existence in enterprises, because they are responsible for specific tasks and provide technical guidance to ordinary management. Moreover, the middle management can also create an efficient working environment for the enterprise and ensure the integrity of the overall structure of the enterprise.

In the process of researching and discussing management, we found that there is a certain connection between some behaviors and psychology of managers, and the self-quality and ability of managers will be limited by objective conditions. In order to further analyze the factors that affect the behavior and psychology of managers, the following theories are now referred to.

3.2.1. High-Level Echelon Theory. In management, it is generally believed that, due to the complexity and randomness of the external environment, it is impossible for managers to form a comprehensive cognition of things [16]. Even if this thing is something that often occurs around managers, managers cannot observe the whole picture of the thing. In this case, the manager's own ability and quality determine the degree of his understanding of relevant things. In other words, once the development of things exceeds the manager's own cognition, the manager's behavior will have a serious impact on the development of the enterprise. During this process, relevant experts and scholars pointed out that, in order to achieve stable development, enterprises need to rebuild the management structure. The theory developed continuously under the influence of management and economics and was finally summarized as the high-level echelon theory. The high-level echelon theory holds that managers with different experiences and life experiences often have different worldviews and values, and these experiences and experiences will constrain management's decision-making. At the same time, these factors will directly affect their communication and cooperation at work and then indirectly affect the relevant decision-making and strategy formulation of enterprises [17].

3.2.2. Imprint Theory. The imprinting theory was first proposed in the field of biology as an animal cognition theory. With the continuous development of biology, people continue to extend and expand this theory and then introduce it into the field of management [18]. In management, imprinting theory no longer emphasizes simple groups; it begins to focus on individuals with special experiences. The theory holds that things and memories with deep impressions will have a lasting effect on an individual's future development, thereby affecting their future thinking and action. In this theory, the so-called special experience refers to an event that an individual has personally experienced or witnessed, which has the characteristics of a wide range of influence, a significant degree of influence, or a long

time continuation. Moreover, with the in-depth study of this theory, it has been found that the occurrence of individual experiences in the sensitive period is an important condition for the formation of individual imprints [19]. Generally, the academic circle mainly defines the sensitive period from two main aspects: one is certain physiological stages of the individual growth period. The second is a period of great changes in the individual growth environment, which mainly includes the period of education, the period of first work, and the period of marriage.

3.2.3. Managerial Short-Term Orientation. On the basis of the above two theories, another theory was found that affects the decision-making of management. In the process of company management, managers often give up making changes and innovations because of the influence of ready-made interests and then depreciate some innovative strategies. After in-depth research on this phenomenon, people call it managerial short-term orientation [20]. Managerial short-term orientation is a corporate management theory that believes that the problem is that market participants, especially institutional investors, emphasize short-term business results, which leads to undervaluation of companies with long-term investment plans. When companies are undervalued, they become attractive targets for other companies or individual investors with substantial discretionary resources. Management's short-term theory believes that, in the actual company management process, the company's managers will inevitably be involved in the whirlpool of shareholders' interests, so this forces the management to reduce enterprise risk investment and the error rate. However, for the benefit of the enterprise, the management has to carry out some daily investment projects, so the management will purposely crack down on long-term investment projects and try to increase the current profit of the company. At the same time, the manager's short-sighted theory also believes that, in the current market environment, short-term investment will be more in line with managers' psychological expectations. If managers engage in long-term strategic investment, it will expose the enterprise to huge risks, and it will also bring risks to their own employment [21].

3.3. K-Means Clustering Algorithm. The process of classifying and dividing more than three objects according to a specific classification method is called clustering. A cluster generated by clustering is a collection of data objects that are similar to objects in the same cluster and different from objects in other clusters. In the process of clustering, the attributes and characteristics between objects are notable signs to judge their differences from other objects and are also one of the references for clustering. In the natural sciences and social sciences, the commonly used statistical method is the cluster analysis method, which is a common analysis method for studying classification and division problems. From a disciplinary point of view, clustering originally belonged to the category of mathematics, but today's clustering methods are not only used in the field of

mathematics, but also widely used in the fields of statistics and information science. However, clustering is not the same as classification. The difference is that people often do not know the specific number of classifications in advance when performing clustering. In the case of simple classification, the classification standards and categories have already been given. The content of cluster analysis is very rich, including systematic clustering method, ordered sample clustering method, dynamic clustering method, fuzzy clustering method, graph theory clustering method, clustering prediction method, and so on [22]. The general formation process of clusters is shown in Figure 3.

Before clustering, people first need to find a sample center point, which is the cluster center. After the center is determined, the data set is automatically divided into different clusters according to the distance and difference between each data point and the cluster center. In the process of cluster formation, the distance between each data point and the center is the similarity between the data and the cluster center, so the similarity between the data sets can be obtained by calculating the distance.

When studying cluster analysis, people often talk about a concept: similarity, which mainly describes the mutual attributes between objects [23]. The closer two things are, the larger their similarity measure is. The farther away two things are, the smaller their similarity measure is. As can be seen from the above, any data set has a natural structure at the bottom, which constitutes the basis of clustering. When a sample set n is given and the sample set stores several attributes of enterprise managers, such as gender, age, education level, and so on, this sample object is then given a m -dimensional attribute, where E_i represents the education level of the i -th object. Figure 4 is a flowchart of the K -means clustering algorithm.

In the process of calculation, there is a certain Euclidean distance between any two objects, which is defined as

$$d = \frac{1}{m} \sqrt{\sum (x_i - x_j)^2}. \quad (1)$$

Among them, i and j represent the i -th and j -th objects, respectively, and x represents the sample space of the object. The Manhattan distance is expressed as

$$d' = \frac{1}{m} \sum_{k=1}^m |x_i - x_j|. \quad (2)$$

In addition to the above two methods that can represent the relationship between arbitrary objects, there are also some indicators that can also be used as a standard for measuring similarity. But no matter how the way of representation changes, the essence of cluster analysis does not change, that is, to find the inherently similar structure between objects.

K -means clustering in the general sense is an adaptive clustering learning algorithm [24]. The operation process of this algorithm is mainly to set up an objective function and then iterate towards the objective function continuously. The representation of the objective function is generally as shown in the following formula:

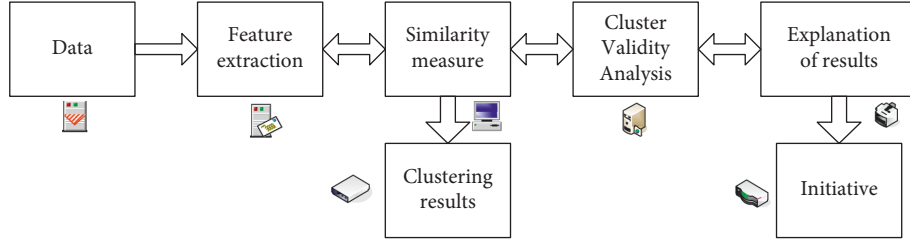


FIGURE 3: Cluster formation process.

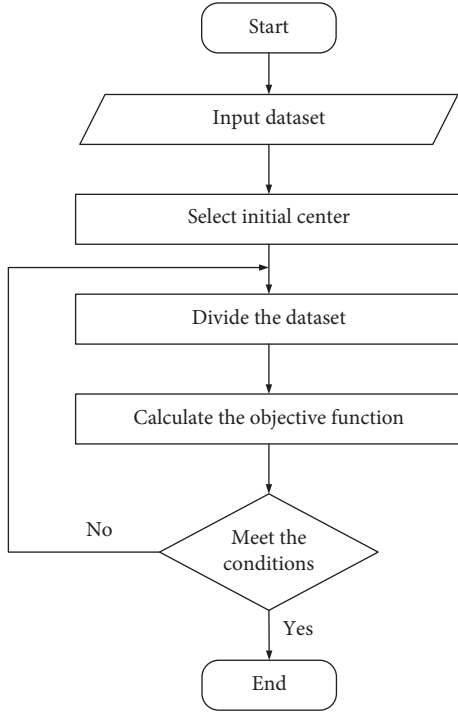


FIGURE 4: Flowchart of K-means clustering algorithm.

$$f = \sum_{j=1}^k \sum_{i=1}^k DIS(X_i, Z_j), \quad (3)$$

$$DIS(X_i, Z_j) = \frac{\left[\sum_{k=1}^n |\omega_i - \omega_j|^2 \right]^{1/2}}{\sqrt{\sum_{k=1}^n (\omega_i - \omega_j)^2}}. \quad (4)$$

Among them, k is the initial cluster center, Z is the cluster center in the adjustment process, and the adjustment operation is as follows:

$$Z_{ij} = \frac{1}{n} \sum_{x_{ij} \in D} x_{ij}. \quad (5)$$

In this formula, x_{ij} represents the j -th value of the sample point at the i -th position, and D is the sample size. However, in many cases, the data is incomplete or the data is too large, which requires us to optimize the above clustering analysis algorithm. On the one hand, characterizing the local similarity between sample data can be done, and on the other hand, the similarity of the data at a certain point needs to be

considered. On this basis, a comprehensive analysis of the sample data can be achieved.

$$\omega_{ij} = F(p_{ij}, q_{ij}), \quad (6)$$

F is the optimized objective function, which in theory we want to decrease as the local similarity increases. In particular, p and q are defined as follows:

$$p_{ij} = p(\Theta_i, \Theta_j) = \left(\frac{\prod_i}{\cos(\theta_t)} \right), \quad (7)$$

$$\cos(\theta_t) = \max_{x_i \in \Theta_i, x_j \in \Theta_j} x_i x_j \cos(\theta_t).$$

In this process, Θ is the tangent space of the sample set, and x_i and x_j express the local structure of the sample points. θ is the angle of the tangent space, which is an adjustable variable.

$$q_{ij} = \prod_{i=1}^d \cos(\theta)^t, \quad (8)$$

$$w_d = \sum_{k=1}^n \cos(\theta)^2 \cdot \prod_{i=1}^k.$$

In the formula, p_{ij} and q_{ij} represent the local similarity and point similarity of the sample data set, respectively. w is the similarity weight derived from the sample tangent space.

Arbitrary similarity weights can form a spectral graph, where the vertices of the graph are formed by the similarity weights of the data. In this case, the aggregation of data is no longer bound by traditional clustering, which can form clusters on arbitrary geometric shapes.

The similarity matrix is constructed as follows:

$$R = \frac{\sum_m \sum_n (A_{mn} - B_{mn})}{\sqrt{\sum_m \sum_n (A_{mn} - B_{mn})^2}},$$

$$A_{mn} = A_{ij} \sum_{i=1, j=1}^n N_{ij}, \quad (9)$$

$$B_{mn} = B_{ij} \sum_{i=1, j=1}^m N_{ij}.$$

In the formula, N is a sample set containing n data nodes, and A_{mn} and B_{mn} are two similarity matrices, respectively.

Similarly, a standardized similarity matrix continues to be constructed to compare its data differences with the general matrix, which is defined as follows:

$$D_{mn} = \sum_j^N W_{ij}. \quad (10)$$

Transform it with a Laplacian matrix to get

$$\begin{aligned} L &= D^{(1/2)} \cdot L \cdot D^{(1/2)}, \\ D &= L - D^{-(1/2)} \cdot W \cdot D^{-(1/2)}, \\ W &= L \cdot L^{-(1/2)} \cdot D^{(1/2)}, \end{aligned} \quad (11)$$

L is a Laplace matrix and W is an identity matrix. After the above process, the maximum eigenvalue of the matrix can be gotten, where D is also called the eigenmatrix.

However, when processing data, problems such as data duplication and inconsistency of attributes are prone to occur in many cases. Therefore, in the actual operation process, the sample data set needs to be modified to delete redundant parts. The modified and normalized definitions of the data are as follows:

$$\begin{aligned} c_i &= \frac{c_i - u}{\sqrt{(1/N) \sum_{i=1}^N (x_i - u)^2}}, \\ u &= \sqrt{c_i \cdot \sum (x_i - \hat{x})^2}. \end{aligned} \quad (12)$$

Among them, the length of the data is N , the normalized value of the data is u , and c_i is any data point in the data set. On the basis of data standardization, the feature matrix needs to continue to be processed to get the following formula:

$$E = D^{(1/2)} \cdot W \cdot L \cdot D^{-(1/2)}. \quad (13)$$

Among them, E is a N -dimensional vector, which describes the basic clustering result of the data, and the matrix W corresponding to the vector is the final clustering result.

Applying the above clustering analysis method can make a simple subdivision of the management of the enterprise. The management division can effectively distinguish which managers can bring long-term benefits and value to the company and which managers can promote enterprise innovation. In the long-term development process of the enterprise, the requirements of the enterprise for the management are gradually transparent. Therefore, after the management is divided, the personal ability and quality of the management will be more prominent. Under the combined effect of the market and economic environment, managers often have some extraordinary skills, so the method of clustering can adapt to different needs.

In the company's internal environment, the management has two purposes, one is to maintain the stability of the company's internal structure, and the other is to ensure the harmony of the company's external environment. The division of the company's management, on the one hand, helps the company's top management to divide the functions of the management, so as to maximize the manager's own

advantages. On the other hand, it can promote the strategic adjustment and personnel adjustment of enterprises. The knowledge and use of the management by the enterprise will magnify the management ability of the manager to continuously meet the needs of enterprise development. When the management repeatedly fails in major decisions, the truth often becomes the target of public criticism. Therefore, managing the management well is more important than managing the employees. Do not let the management be the messenger. From another point of view, the segmentation of enterprise management can be divided into two levels: macrodivision and microdivision. Among them, the macrodivision mainly refers to the subdivision of enterprises according to the business ability of managers and the quality of managers themselves. For example, managers are divided into senior managers, intermediate managers, and general managers according to their educational level. However, this kind of division in the macrosense is mostly the division of a single variable, so on this basis, people put forward microsegmentation. Microdivision also refers to behavioral subdivision. Generally, the results of microdivision are more detailed and complex. For example, managers can be divided into aggressive managers, stable managers, and conservative managers according to their investment behaviors. In the process of this research, not only do the goals need to be set in advance, but also a lot of data need to be analyzed. Figure 5 shows the empirical research process of this paper.

Compared with general research and analysis methods, such as single variable segmentation, behavioral segmentation, or simple macroanalysis, K-means clustering can fit well with the objective function, and the process of dividing does not involve any personal subjective emotions. Therefore, this classification method can more objectively reflect the differences between the target objects. Moreover, when studying the characteristics and application effects of target objects, K-means-based clustering is beneficial to thoroughly understand the segmentation results and to establish a good partition model between objects and targets in advance. In the process of studying the technological innovation of enterprises, the level of education of the company's management is used as the basis for the division, and the management's own ability and literacy are used as the auxiliary division criteria, which can make the research more in-depth and can also fully grasp the company's management quality, personal quality, education level, and innovation ability. On this basis, the company will be able to further clarify the management hiring standards and continue to carry out technological innovation practices under the leadership of the new management.

4. Segmentation of Management Education Based on K-Means Clustering Algorithm

Before the empirical research begins, it is necessary to conduct statistics and analysis on the collected sample data and divide the research objectives according to the K-means clustering algorithm. The statistical results of different variables of the whole sample are shown in Table 1.

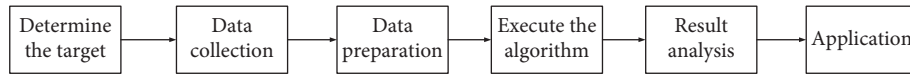


FIGURE 5: Empirical research process.

TABLE 1: Statistical results of different variables in the whole sample.

Variable	Sample size	Mean	Standard deviation	Median
RD	12387	0.030	0.031	0.027
SIZE	12387	21.721	1.152	21.580
LEV	12387	0.410	0.201	0.410
ROA	12387	0.042	0.052	0.049
SEX	12387	0.949	0.223	1
E-HIGH	12387	0.851	0.621	0
E-LOW	12387	0.550	1.382	0.639

TABLE 2: Statistics grouped by managers' education.

Variable	Managers with high education background			Managers without high education background		
	Mean	Standard deviation	Median	Mean	Standard deviation	Median
SIZE	21.334	21.721	21.152	21.591	1.151	21.582
LEV	0.364	0.411	0.201	0.421	0.205	0.404
ROA	0.045	0.048	0.052	0.039	0.055	0.521
SEX	0.897	0.949	0.223	0.952	0.219	1
PATENT	19.111	1.218	0.348	11.210	0.821	0.312
INNOVATION INPUT	12.987	2.314	1.167	9.345	1.213	0.921
INNOVATION OUTPUT	11.321	2.113	0.921	7.611	1.324	0.816

In Table 1, the factors that affect the technological innovation of enterprises are collected, and their impact on the technological innovation of enterprises is calculated. Among them, the variance of the impact of education level on enterprise technological innovation is 0.851, and the variance of the impact of production scale on enterprise technological innovation is 21.721, which indicates that the impact of education level on enterprise technological innovation is relatively stable. However, the educational level of enterprises is not equal to the educational level of managers, so we will analyze the educational level of managers next. The grouping of managers' educational status and their impact on enterprises are shown in Table 2 and 3.

From the above data, it can be known that the manager's educational background coefficient is 0.010, and with the continuous improvement of the manager's educational level, the correlation coefficient is increasing and showing a significant positive feature, with the highest coefficient being 1.76. This shows that the higher the education level of managers, the more likely it will promote enterprises to invest in technological innovation.

In order to explore the influence of the educational background of different levels of management on the technological innovation of enterprises, regression analysis was carried out on the educational background of the general manager and chairman of the board, respectively. Table 4 and 5 are its regression results.

The data shows that different management levels will have different impacts on the technological innovation of

TABLE 3: The impact of higher education background on the investment in scientific and technological innovation of enterprises.

Variable	Correlation coefficient	University	Master	Phd
EDUCATION	0.010	0.004	0.006	0.016
HIGH EDUCATION	1.76	2.92	3.08	3.00
STUDY ABROAD	0.022	0.014	0.201	0.004
RESEARCH INSTITUTE	6.49	7.70	0.052	0.0006
CLUB	0.011	7.89	7.91	7.62
CONSTANT	3.871	2.63	2.66	3.98
ABILITY	-14.82	-5.13	-5.11	-5.05

TABLE 4: The regression results of the influence of the general manager's educational background on the technological innovation of enterprises.

Variable	Company innovation performance			
	Patent	RD	Input	Output
MASTER	0.462	-0.92	1.01	0.70
STUDY ABROAD	0.512	-0.014	1.201	1.004
RESEARCH INSTITUTE	0.351	-0.70	2.052	2.531
UNIVERSITY	0.019	-0.89	1.91	0.62
FAMOUS SCHOOL	1.112	-0.63	1.66	1.98
PHD	4.82	-1.13	6.11	5.05

enterprises. Among them, if the general manager's education level is higher, it will promote the enterprise to implement the innovation-driven strategy, and its highest correlation

TABLE 5: The regression results of the influence of the chairman’s educational background on the technological innovation of enterprises.

Variable	Company innovation performance			
	Patent	RD	Input	Output
MASTER	1.121	-0.11	1.19	1.77
STUDY ABROAD	1.005	-0.914	1.43	1.65
RESEARCH INSTITUTE	0.621	-1.20	2.001	2.901
UNIVERSITY	0.005	-1.50	0.22	0.62
FAMOUS SCHOOL	1.219	-0.23	2.66	3.98
PHD	-3.221	-1.11	3.12	3.05

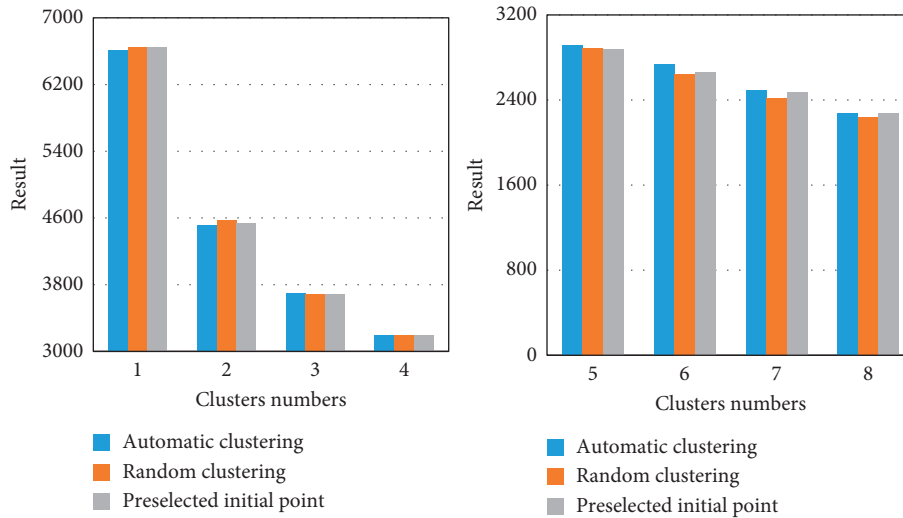


FIGURE 6: Clustering results of different initial points.

coefficient reaches 4.82. The higher education level of the chairman may inhibit the company’s technological innovation, and its highest coefficient is -3.221 , which shows that it has a significant negative correlation. The reason is that the chairman of the board is the shareholder of the company and the direct beneficiary of the company’s immediate interests, so it will hinder the company’s innovation to a certain extent. The general manager is generally an external employee of the company, and his income is directly related to the company’s income, so it is in line with his interests to promote innovation.

5. Final Clustering Results

In the actual clustering operation process, different initial points will affect the clustering results. Therefore, for the rationality of the management division, it is necessary to minimize the impact of clustering. Figure 6 shows the clustering results of different initial points.

Figure 6 shows that when the number of clustering is relatively low, there are relatively more clustering results; in particular, after only one clustering, the clustering results are as many as 6300. However, when the number of clustering reaches 7, the clustering results tend to be stable, and the numerical results fluctuate around 2400. At this time, the clustering results have the lowest impact on the management division.

However, within the clusters divided according to the educational level of the management, the gap in the educational level of the management will bring errors to the analysis of the clustering. The intraclass residual is a measure used to describe the clustering error, and the smaller the sum of squares is, the smaller the error is. The intraclass residual sum of squares for different initial points is shown in Figure 7.

As can be seen from Figure 7, as the number of clusters increases, different initial point clusters begin to recombine 10 times. It can be clearly found that the second clustering and the tenth clustering are two obvious watersheds, and the number of clusters in the second watershed has dropped to 4000. In the tenth clustering, the number of clusters decreased from 2200 to about 2000.

After ensuring that the division of management education level will not bring errors and influences to its research, its correlation with corporate technological innovation will be analyzed emphatically. The correlation between management education and corporate technological innovation is shown in Figure 8.

The experiment in Figure 8 shows that managers with higher educational backgrounds approve companies to adopt more means for technological innovation. Among them, the correlation coefficient between technological innovation investment and management with high education background is 1.521, and the correlation coefficient

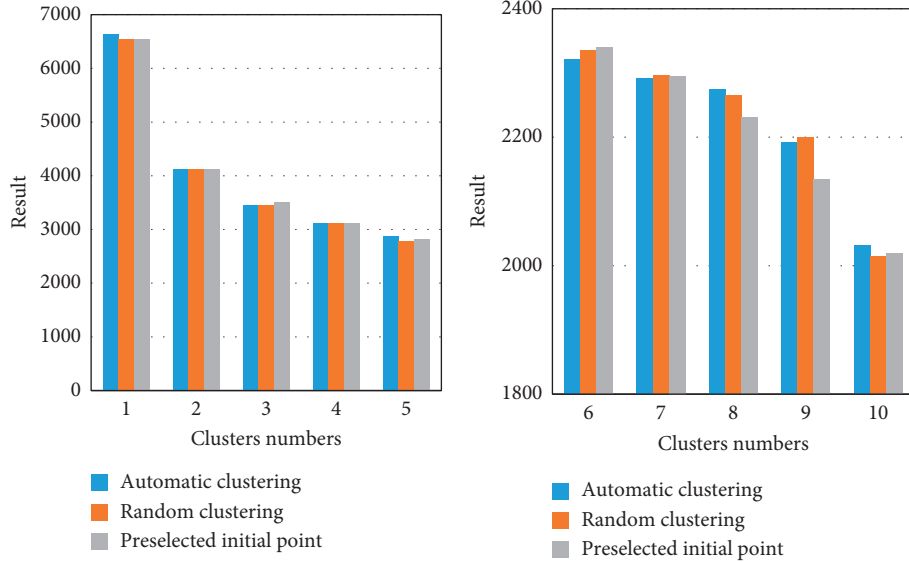


FIGURE 7: Intra-class residual sum of squares for different initial points.

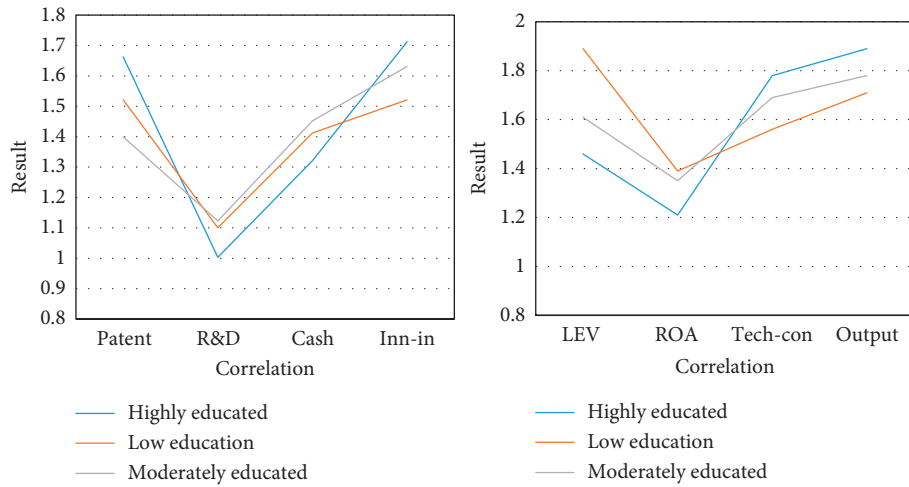


FIGURE 8: Correlation between management education and corporate technological innovation.

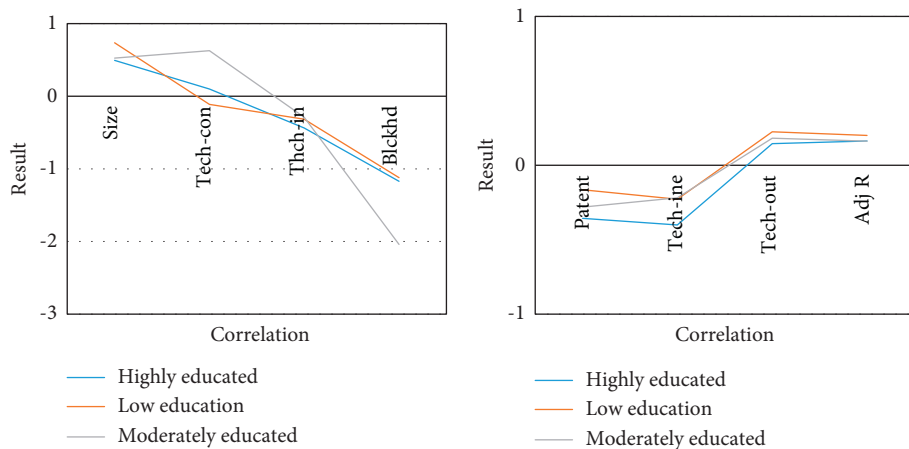


FIGURE 9: Robustness test between management education and corporate technological innovation.

between it and the number of patent applications is 1.662. This fully demonstrates that management with a higher education background will promote technological innovation in enterprises.

Using only the number of patent applications to measure the correlation between a firm's technological innovation and management education can lead to a severe left-biased effect. Therefore, other variables are added to the above correlation test, and the least squares method is used to test the robustness of the correlation. The robustness test results between management education and corporate technological innovation are shown in Figure 9.

It can be seen from Figure 9 that the regression coefficient between corporate innovation input and management with high education background is -0.164 , and the regression coefficient between corporate innovation input and output and management with higher education is -0.221 . And it also exhibits significant negative characteristics at the 1% horizontal level, which fully demonstrates the robustness and reliability of the above correlation conclusion.

6. Conclusions

Starting from the educational level of enterprise management, this paper firstly analyzed the influencing factors of enterprises' technological innovation and the related theories of enterprise management. On this basis, the article then divided the management education level into clusters based on the K-means clustering algorithm and conducted an empirical study on its influence on the technological innovation of enterprises. Experiments showed that management with a high education background tended to promote the practice of scientific and technological innovation in enterprises. However, due to time reasons, the article did not study the education time of enterprise management during the experiment, so the research lacked comprehensiveness. In the future, the paper will comprehensively study the time and current situation of management education and continue to fill in the research gaps.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

Acknowledgments

This work was supported by Research Project of "13th Five-Year Plan" of Education Bureau of Guangdong, China (Project no. 2020GXJK233); Foundation for Young Innovative Talents of Colleges and Universities of Guangdong, China (Project no. 2020WQNCX244); Research Project of "13th Five-Year Plan" of Education Bureau of Guangdong, China (Project no. 2020GXJK252); and 2020 Key Scientific

Research Platform Project of Higher Education of Guangdong, China (Project no. 2020CJPT029).

References

- [1] J. Yang, Y. Qin, and F. Moulaert, "The influence of employee pressure on the management cost of enterprise technological innovation using mental health education," *Work*, vol. 70, no. 4, pp. 1–10, 2021.
- [2] Z. Liu, R. Mu, S. Hu, L. Wang, and S. Wang, "Intellectual property protection, technological innovation and enterprise value—An empirical study on panel data of 80 advanced manufacturing SMEs," *Cognitive Systems Research*, vol. 52, no. 12, pp. 741–746, 2018.
- [3] Q. Zhang, S. Liu, D. Gong, and Q. Tu, "A latent-dirichlet-allocation based extension for domain ontology of enterprise's technological innovation," *International Journal of Computers, Communications & Control*, vol. 14, no. 1, pp. 107–123, 2019.
- [4] J. Chen, S. Lin, and M. Jin, "Learning to use the symbiosis behavior: the mediating effect between enterprise innovation network and technological innovation performance," *Centre Calling*, vol. 42, no. 3, pp. 1222–1229, 2017.
- [5] Z. Wang, K. Wang, S. Pan, and Y. Han, "Segmentation of crop disease images with an improved K-means clustering algorithm," *Applied Engineering in Agriculture*, vol. 34, no. 2, pp. 277–289, 2018.
- [6] Z. Khan, "An improved K-means clustering algorithm based on an adaptive initial parameter estimation procedure for image segmentation," *International journal of innovative computing, information & control: IJICIC*, vol. 13, no. 5, pp. 1509–1525, 2017.
- [7] W. Li, J. Y. Zhao, and T. S. Yan, "Improved K-means clustering algorithm optimizing initial clustering centers based on average difference degree," *Kongzhi yu Juece/Control and Decision*, vol. 32, no. 4, pp. 759–762, 2017.
- [8] S. Allen, A. L. Cunliffe, and M. Easterby-Smith, "Understanding sustainability through the lens of ecocentric radical-reflexivity: implications for management education," *Journal of Business Ethics*, vol. 154, no. 3, pp. 781–795, 2017.
- [9] M. Kolb, L. Fröhlich, and R. Schmidpeter, "Implementing sustainability as the new normal: responsible management education from a private business school's perspective," *International Journal of Management in Education*, vol. 15, no. 2, pp. 280–292, 2017.
- [10] N. Nikolova and L. Andersen, "Creating shared value through service-learning in management education," *Journal of Management Education*, vol. 41, no. 5, pp. 750–780, 2017.
- [11] D. Howell, T. Harth, J. Brown, C. Bennett, and S. Boyko, "Self-management education interventions for patients with cancer: a systematic review," *Supportive Care in Cancer*, vol. 25, no. 4, pp. 1323–1355, 2017.
- [12] S. M. Holliday, C. Hayes, A. J. Dunlop et al., "Does brief chronic pain management education change opioid prescribing rates? A pragmatic trial in Australian early-career general practitioners," *Pain*, vol. 158, no. 2, pp. 278–288, 2017.
- [13] M. Thangamani, R. Vijayalakshmi, M. Ganthimathi, M. Ranjitha, P. Malarkodi, and S. Nallusamu, "Efficient classification of heart disease using KMeans clustering algorithm," *International Journal of Engineering Trends and Technology*, vol. 68, no. 12, pp. 48–53, 2020.
- [14] N. A. Khairani and E. Sutoyo, "Application of K-means clustering algorithm for determination of fire-prone areas utilizing hotspots in west kalimantan province," *International*

- Journal of Advances in Data and Information Systems*, vol. 1, no. 1, pp. 9–16, 2020.
- [15] T. Santoso and F. Saftarina, “Clusterization of paddy field farmers condition in kota metro lampung province Indonesia using K-means clustering algorithm,” *Journal of Agribusiness and Community Empowerment*, vol. 3, no. 1, pp. 37–43, 2020.
- [16] Y. Yang, B. Qian, Q. Xu, and Y. Yang, “Climate regionalization of asphalt pavement based on the K-means clustering algorithm,” *Advances in Civil Engineering*, vol. 2020, no. 4, Article ID 6917243, 13 pages, 2020.
- [17] S. Yin and T. Wang, “An unknown Protocol improved k-means clustering algorithm based on Pearson distance,” *Journal of Intelligent and Fuzzy Systems*, vol. 38, no. 4, pp. 4901–4913, 2020.
- [18] B. Sarada, “Enhanced evolutionary computing assisted K-means clustering algorithm for BigData analytics,” *International Journal of Advanced Trends in Computer Science and Engineering*, vol. 9, no. 4, pp. 6007–6017, 2020.
- [19] X. Lin and J. Xu, “Road network partitioning method based on Canopy-Kmeans clustering algorithm,” *Archives of Transport*, vol. 54, no. 2, pp. 95–106, 2020.
- [20] M. Bhardwaj, “Improved K-means clustering algorithm based on KD-tree approach,” *Bioscience Biotechnology Research Communications*, vol. 13, no. 14, pp. 160–163, 2020.
- [21] X. He, J. Li, B. Wang et al., “Diabetes self-management education reduces risk of all-cause mortality in type 2 diabetes patients: a systematic review and meta-analysis,” *Endocrine*, vol. 55, no. 3, pp. 712–731, 2017.
- [22] U. Srilakshmi, N. Veeraiah, Y. Alotaibi, S. A. Alghamdi, O. I. Khalaf, and B. V. Subbayamma, “An improved hybrid secure multipath routing protocol for MANET,” *IEEE Access*, vol. 9, Article ID 163043, 2021.
- [23] M. Nasir, “A novel fuzzy clustering with metaheuristic based resource provisioning technique in cloud environment,” *Fusion: Practice and Applications*, vol. 6, no. 1, pp. 08–16, 2021.
- [24] M. Shafiabadi, Z. Ahmadi and M. R. Esfandiyari, “Solving the problem of target k-coverage in WSNs using fuzzy clustering algorithm,” *Journal of Intelligent Systems and Internet of Things*, vol. 2, no. 2, pp. 55–76, 2021.